

Appendix A

Comparison of the SEMWISE and MLM analysis approaches

This appendix compares the SEMWISE and multi-level modeling (MLM) approaches in terms of data setup, data analysis, and (interpretation of) results as applied to the stylized example shown in Figure 1 of the main text. Figure A1 shows how the data file is structured in the MLM approach (left-hand panel) compared to the SEMWISE approach (right-hand panel), using the four responses of the fictitious respondent in Figure 1 in the main text as an example.

Multilevel data setup				
Respondent	Profile	Profile warmth	Profile competence	Rating
1	1	1	-1	2
1	2	-1	1	4
1	3	1	1	5
1	4	-1	-1	1
2	1
2	2
...

SEMWISE data setup				
Respondent	Rating for profile 1	Rating for profile 2	Rating for profile 3	Rating for profile 4
1	2	4	5	1
2
3

Figure A1. Data setup in a simplified policy capturing study.

As shown in Figure A1, in the MLM dataset, respondents' reactions to the four profiles (obtained by crossing the two levels of warmth with the two levels of competence) are specified on four separate lines of data (i.e., each line represents the rating of one profile, with multiple lines for each respondent). In addition, the profile attribute levels are represented by two additional variables, one containing the effect-coded attribute levels for warmth for each profile, the other containing the effect-coded attribute levels for competence for each profile. The profiles' attribute levels are repeated across respondents, but the ratings are respondent-specific. For the SEMWISE approach, each participant has one line of data and there are four columns of ratings corresponding to the ratings of the four profiles. In other words, MLM requires data in long format, SEMWISE requires data in wide format. In

the SEMWISE approach, the attribute levels of the profiles are not part of the dataset but are specified as fixed model parameters in the analytical model (see the loadings in Figure 1).

In the MLM approach, the ratings of the teammate profiles are regressed on each profile's warmth and competence level, where (for the sake of this example) effect coding is used to represent the profiles (i.e., -1 represents a low level, $+1$ represents a high level of an attribute). The estimated regression coefficients are the weights (or utilities) that respondents attach to warmth and competence, which are inferred from the overall ratings of the profiles. In other words, the overall rating of a profile is decomposed into the weights of the attribute levels that characterize the profile. It can be shown that when using MLM, the estimated regression coefficients, which are allowed to vary across respondents, are a compromise between (or weighted combination of) two types of regressions, a pooled regression and individual-level regressions (Gelman & Hill, 2007). In a pooled regression, it is assumed that all respondents assign the same weights to warmth and competence when rating teammates, so the regression coefficients are fixed to be equal across respondents. In an individual-level regression, it is assumed that each respondent assigns idiosyncratic weights to warmth and competence when rating teammates, so a separate regression equation is estimated for each respondent across the rated profiles (four in the present case). If there is little variability in coefficients across respondents, the MLM estimates will be close to the pooled estimates, but as the variability in coefficients across respondents increases, the MLM estimates move toward the individual-level estimates. The advantage of the MLM regression coefficients is that, on the one hand, the limiting assumption of effect homogeneity is relaxed and that, on the other hand, the estimates tend to be more stable than the individual-level regression coefficients (which are often based on a relatively small number of distinct profiles).

In the SEMWISE approach, the estimated weights are the same as in the MLM approach, but the way in which the model is specified and the weights are estimated is quite different. Instead of regressing teammate ratings on warmth and competence, one specifies a

factor model in which the ratings of the four experimental profiles are treated as the observed indicators of three latent factors: an intercept factor, a weight factor for warmth, and a weight factor for competence. In order to estimate a factor model, the data have to be structured differently, as shown in Figure A1.

Although the SEMWISE model is a factor model, it should be noted that the SEMWISE factor model differs from a conventional factor model in that the factor loadings are fixed to particular values (analogous to the effect-coded independent variables in the MLM approach) and each indicator (i.e., each profile rating) loads on multiple factors, the reason being that each profile rating is assumed to be a function of the conjoint effect of multiple weight factors (e.g., the rating of the profile with high warmth and high competence depends on the weight that respondents attach to warmth and the weight that respondents attach to competence).

The weight factor scores in the SEMWISE approach are identical to the regression coefficients estimated in the MLM approach. Specifically, the latent intercept factor captures the average rating that each respondent gives to the entire set of profiles. The latent intercept factor has unit loadings on the four indicators (the ratings of the four profiles) and corresponds to the intercept term in the MLM approach. The four profile ratings have loadings on the latent warmth and competence weight factors, and these loadings correspond to the profiles' effect codes (for warmth and competence) in the MLM approach. Thus, both approaches model each profile rating as a function of its effect-coded attribute levels and the respective weights (regression coefficients in MLM, weight factor scores in SEMWISE) of these attribute levels. Since the loadings are effect-coded as -1 for low and $+1$ for high warmth and competence, respectively, twice the estimated factor score is the difference in the weight attached to low and high warmth or competence.

Below we provide Mplus syntax to simulate data corresponding to the example shown in Figure 1 and to analyze the data in an equivalent way using either SEMWISE or MLM

(see Figure A1). The Mplus output shows that the parameter estimates are the same across the MLM and SEMWISE analyses, although the terminology differs across approaches.

1. Data generation

```
TITLE: Data generation for SEMWISE vs. MLM (Fig 1 and Fig A1);
MONTECARLO:
NAMES = y1-y4;                !response variables: profile rating;
NOBS = 250;                   !sample size
SAVE = example_wide.dat;      !generated data filename
SEED = 0;                     !results can be replicated exactly
MODEL POPULATION:            !true model for data generation
icept BY y1-y4@1;             !intercept factor
wfwarm BY y1@1 y2@-1 y3@1 y4@-1; !weight factor for warmth
wfcomp BY y1@-1 y2@1 y3@1 y4@-1; !weight factor for competence
icept*.7 wfwarm*.7 wfcomp*.7; !factor variances are .7
icept WITH wfwarm*.1;        !factor covariance
icept WITH wfcomp*.1;        !factor covariance
wfwarm WITH wfcomp*.1;       !factor covariance
y1-y4*.2;                    !residual variance of response
variable
[y1-y4@0];                   ! intercepts of response variable
[icept*3 wfwarm*.6 wfcomp*.3]; !intercept and weight factor means
MODEL: y1-y4 with y1-y4;     !observed sample covariances
```

2. Data analysis using the SEMWISE approach

```
TITLE: SEMWISE analysis for the example in Figures 1 and 2;
DATA: FILE = example_wide.dat; !use the data in wide format
VARIABLE: NAMES = y1-y4;      !response variables
MODEL:
icept by y1-y4@1;             !intercept factor
wfwarm by y1@1 y2@-1 y3@1 y4@-1; !weight factor for warmth
wfcomp by y1@-1 y2@1 y3@1 y4@-1; !weight factor for competence
[y1-y4@0];                   !response intercepts are set to zero
[icept wfwarm wfcomp];       !freely estimated factor means
y1-y4(e);                    !residual variances equal for
correspondence with MLM
OUTPUT: TECH1 STANDARDIZED;   !standardized keyword gives R2
```

3. Data analysis using the MLM approach

```
Title: Multilevel modeling (MLM) analysis for Figures 1 and 2;
data: file = example_wide.dat;
DATA WIDETOLONG:
  WIDE = y1-y4 | W1-W4 | C1-C4;
  LONG = y | xwarm | xcomp;
  IDVARIABLE = person;
  REPETITION = profile;
VARIABLE: names = y1 y2 y3 y4;
          usevar = W1 W2 W3 W4 C1 C2 C3 C4 y xwarm xcomp person;
          AUXILIARY = W1 W2 W3 W4 C1 C2 C3 C4;
cluster = person;
within = xwarm xcomp;
DEFINE:
  W1 = 1;
  W2 = -1;
  W3 = 1;
  W4 = -1;
  C1 = -1;
```

```

C2 = 1;
C3 = 1;
C4 = -1;
analysis: type = random twolevel;
          estimator = ml;

model:
%within%
wfwarm | y on xwarm;
wfcomp | y on xcomp;
%between%
wfwarm wfcomp;
y;
wfwarm with y;
wfcomp with y wfwarm;

```

4. Selected output for both approaches

SEMWISE					MLM				
	Est.	S.E.	t	p		Est.	S.E.	t	p
WFARM WITH					Between Level				
ICEPT	0.138	0.049	2.815	0.005	WFARM WITH	0.138	0.049	2.819	0.005
WFCOMP WITH					WFCOMP WITH				
ICEPT	0.118	0.048	2.451	0.014	Y	0.118	0.046	2.565	0.010
WFARM	0.136	0.049	2.788	0.005	WFARM	0.136	0.054	2.497	0.013
Means					Means				
ICEPT	3.036	0.055	55.193	0.000	Y	3.036	0.055	55.192	0.000
WFARM	0.545	0.055	9.855	0.000	WFARM	0.545	0.055	9.854	0.000
WFCOMP	0.294	0.055	5.364	0.000	WFCOMP	0.294	0.055	5.363	0.000
Variances					Variances				
ICEPT	0.707	0.068	10.434	0.000	Y	0.707	0.066	10.661	0.000
WFARM	0.715	0.069	10.442	0.000	WFARM	0.715	0.065	10.992	0.000
WFCOMP	0.700	0.067	10.426	0.000	WFCOMP	0.700	0.069	10.185	0.000
Residual Variances					Within Level				
Y1	0.196	0.018	11.180	0.000	Residual Variances				
Y2	0.196	0.018	11.180	0.000	Y	0.196	0.016	12.575	0.000
Y3	0.196	0.018	11.180	0.000					
Y4	0.196	0.018	11.180	0.000					

Appendix B

Correlation matrix for empirical application 1

	1	2	3	4	5	6	7	8
1 Female								
2 HHL	.009							
3 HLL	.039	.481						
4 HHH	-.023	.420	.297					
5 HLH	-.062	.222	.376	.418				
6 LHL	.055	.547	.382	.358	.103			
7 LLL	.027	.432	.585	.280	.344	.415		
8 LHH	.043	.415	.337	.556	.337	.418	.289	
9 LLH	.045	.169	.398	.362	.595	.188	.459	.414

Note: Correlations based on data setup in wide format (responses to the experimental profiles correspond to variables 2 to 9). Female refers to respondent gender (0 = male, 1 = female). The other variable names refer to the levels (L = low, H = high) of the three attributes attractiveness, warmth and competence.

Appendix C

Correlation matrix of empirical application 2

	y1	y2	y3	y4	y5	y6	y7	y8	z1	z2	z3	z4	z5	z6	z7	z8	EC1	EC2	EC3	EC4	EC5	EC6	IM1	IM2	IM3	IM4	IM5	IM6	IM7	IM8	IM9	IM10					
y2	.22																																				
y3	.15	.22																																			
y4	.27	.28	.23																																		
y5	-.08	.22	.16	.16																																	
y6	.13	.09	.12	.17	.13																																
y7	.15	.14	-.07	.17	.24	.37																															
y8	.18	.25	.08	-.07	.18	.10	.22																														
z1	.67	.30	.19	.26	.04	.12	.16	.24																													
z2	.25	.74	.25	.25	.25	.13	.14	.22	.50																												
z3	.14	.27	.69	.22	.16	.13	-.03	.09	.38	.44																											
z4	.23	.28	.22	.75	.21	.19	.15	.01	.40	.44	.38																										
z5	-.04	.17	.14	.15	.77	.17	.20	.14	.15	.37	.29	.37																									
z6	.17	.14	.19	.21	.14	.75	.31	.13	.34	.33	.40	.35	.30																								
z7	.18	.17	-.07	.17	.26	.40	.79	.24	.32	.32	.08	.30	.37	.46																							
z8	.19	.24	.13	.02	.26	.14	.24	.70	.45	.37	.30	.22	.36	.36	.40																						
EC1	-.19	.05	.15	.06	.15	-.10	-.23	-.08	-.15	.04	.09	.07	.11	-.12	-.19	-.08																					
EC2	-.13	.03	.18	.06	.08	-.16	-.28	-.13	-.11	.03	.09	.07	.07	-.15	-.29	-.11	.60																				
EC3	-.17	.07	.13	.02	.15	-.14	-.26	-.13	-.16	.06	.06	.06	.14	-.15	-.26	-.11	.46	.48																			
EC4	.03	-.15	-.18	-.18	-.18	.12	.24	.13	.04	-.11	-.10	-.16	-.15	.11	.23	.14	-.45	-.48	-.39																		
EC5	.08	-.09	-.10	-.11	-.11	.09	.25	.11	.00	-.14	-.11	-.18	-.13	.08	.22	.09	-.36	-.37	-.28	.39																	
EC6	.11	-.18	-.21	-.12	-.14	.18	.31	.12	.09	-.14	-.14	-.12	-.15	.14	.29	.09	-.47	-.57	-.51	.56	.46																
IM1	-.05	.04	.03	.03	.10	-.08	.02	-.03	-.09	-.04	-.03	-.03	.07	-.09	-.02	-.06	.07	.07	.12	.05	.04	-.03															
IM2	-.02	-.10	-.08	-.08	.06	.03	-.02	.01	.05	-.02	-.04	-.06	.03	.02	.07	.03	.02	-.04	-.03	-.01	-.05	.10	-.25														
IM3	-.06	.07	.08	.04	.07	.02	-.06	.01	.01	.07	.00	.03	.07	-.03	.00	.06	.16	.11	.11	-.10	-.03	-.12	-.08	.19													
IM4	.04	.02	-.02	.10	-.05	.03	-.01	-.08	.05	.02	-.07	.07	-.04	-.01	.00	.00	.00	-.09	-.01	.06	.10	.11	.15	.04	.03												
IM5	.01	-.02	.03	.05	-.04	-.04	-.01	-.06	-.04	.01	.00	.06	-.04	-.04	.03	-.03	.09	.11	.20	-.10	.03	-.07	.01	.10	.12	-.02											
IM6	.01	.03	.04	-.01	-.07	.03	.03	.03	-.03	-.03	-.03	.04	-.03	-.03	.03	.00	-.02	.07	.07	-.06	.09	-.04	.05	-.06	-.09	.07	.02										
IM7	-.05	-.07	.06	.02	-.03	.04	-.04	-.04	-.08	-.06	.06	.00	.04	.05	-.02	-.08	.04	.09	.10	.04	.04	-.06	.27	-.18	-.17	.02	.04	.13									
IM8	.02	.05	-.03	-.01	.08	-.07	.11	.09	.03	.03	-.02	-.01	.10	-.07	.09	.06	-.10	-.15	-.02	.15	.09	.17	.25	-.09	-.11	.16	.00	.04	.09								
IM9	-.03	.01	-.07	-.09	.00	-.05	.00	.06	-.01	.06	-.09	.00	.01	-.05	.04	.11	.07	.00	.12	-.01	-.07	-.03	-.13	.24	.36	-.01	.17	-.11	-.36	-.08							
IM10	-.05	-.10	.06	.00	.03	.00	-.09	-.11	-.04	-.03	.04	.04	.03	.02	-.09	-.09	.17	.22	.14	-.11	-.18	-.12	-.10	.23	.21	-.22	.27	-.04	-.02	-.01	.20						

Note: Correlations based on data setup in wide format. Variables y1-y8 refer to profile ratings using the first item ('To what extent would you like to work for this company?' rated by manipulating a sliding bar linked to a smiley face with five levels ranging from 1= low to 5=high), z1-z8 to profile ratings using the second item ('How attractive do you find this company?' rated by means of a continuous sliding scale marked by five stars with scores ranging from zero to five). EC1-EC6 refer to the Environmental Concern scale items, IM1-IM10 to the Impression Management scale items.

Appendix D

Mplus, R, and LISREL syntax for analyzing the data of the SEMWISE core model and several extensions

This web appendix provides Mplus syntax for generating artificial data and Mplus, R, and LISREL syntax for analyzing the data of the SEMWISE core model and several extensions.

Mplus data generation	Mplus data analysis	R data analysis	LISREL data analysis
<pre>!Example 1 data generation; Title: SEMWISE core model data generation (see Figure 2); montecarlo: names = y1-y8; nobs = 500; save = semwise_core.dat; model population: eta0 by y1-y8@1; eta1 by y1@1 y2@1 y3@1 y4@1 y5@-1 y6@-1 y7@-1 y8@-1; eta2 by y1@-1 y2@-1 y3@1 y4@1 y5@-1 y6@-1 y7@1 y8@1; eta3 by y1@1 y2@-1 y3@1 y4@-1 y5@1 y6@-1 y7@1 y8@-1; eta0-eta3*.7; eta0 with eta1*.1; eta0 with eta2*.1; eta0 with eta3*.1; eta1 with eta2*.1; eta1 with eta3*.1; eta2 with eta3*.1; y1-y8*.2;</pre>	<pre>!Example 1 data analysis; Title: SEMWISE core model data analysis (see Figure 2); data: file = semwise_core.dat; variable: names = y1-y8; model: eta0 by y1-y8@1; eta1 by y1@1 y2@1 y3@1 y4@1 y5@-1 y6@-1 y7@-1 y8@-1; eta2 by y1@-1 y2@-1 y3@1 y4@1 y5@-1 y6@-1 y7@1 y8@1; eta3 by y1@1 y2@-1 y3@1 y4@-1 y5@1 y6@-1 y7@1 y8@-1; eta0-eta3*.7; eta0 with eta1*.1; eta0 with eta2*.1; eta0 with eta3*.1; eta1 with eta2*.1; eta1 with eta3*.1; eta2 with eta3*.1; y1-y8*.5; [y1-y8@0]; [eta0-eta3];</pre>	<pre>#Example 1 data analysis; #SEMWISE core model data analysis #(see Figure 2); library(lavaan) semwise_core <- read.table("semwise_core.dat") names(semwise_core)<- c("y1","y2","y3","y4","y5","y6","y7","y8") model <- ' eta0=~1*y1+1*y2+1*y3+1*y4+1*y5+1*y6+1*y7 +1*y8 eta1=~1*y1+1*y2+1*y3+1*y4+-1*y5+-1*y6+- 1*y7+-1*y8 eta2=~-1*y1+-1*y2+1*y3+1*y4+-1*y5+- 1*y6+1*y7+1*y8 eta3=~1*y1+-1*y2+1*y3+-1*y4+1*y5+- 1*y6+1*y7+-1*y8 y1 -0*1 y2 -0*1 y3 -0*1 y4 -0*1 y5 -0*1 y6 -0*1 y7 -0*1 y8 -0*1 eta0-1</pre>	<pre>!Example 1 data analysis; SEMWISE core model data analysis (see Figure 2) DA NI=8 NO=0 LA y1 y2 y3 y4 y5 y6 y7 y8 RA FI= semwise_core.dat MO NY=8 NE=4 LY=FI TE=DI,FR AL=FR PS=SY,FR BE=ZE TY=ZE MA LY 1 1 -1 1 1 1 -1 -1 1 1 1 1 1 1 1 -1 1 -1 -1 1 1 -1 -1 -1 1 -1 1 1 1 -1 1 -1 LE eta0 eta1 eta2 eta3 OU MI SC</pre>

		<pre>eta1~1 eta2~1 eta3~1 '</pre> <pre>fit <- sem(model, data=semwise_core, meanstructure = TRUE) summary(fit)</pre>	
<pre>!Example 2 data generation; Title: Data generation with attributes: Three brands offered at three (non-linear) price levels; montecarlo: names = y1-y9; nobs = 500; save = semwise_nonbinary.dat; model population: brand2 by y1@-1 y2@-1 y3@-1 y4@1 y5@1 y6@1 y7@0 y8@0 y9@0; brand3 by y1@-1 y2@-1 y3@-1 y4@0 y5@0 y6@0 y7@1 y8@1 y9@1; price by y1@-1 y2*0.2 y3@1 y4@-1 y5*0.2 y6@1 y7@-1 y8*0.2 y9@1; brand2-brand3*.9 price*.9; brand2 with brand3*0.1; brand2 with price*-.1; brand3 with price*.1; y1-y9*.2;</pre>	<pre>!Example 2 data analysis; Title: nonbinary SEMWISE analysis; variable: names = y1-y9; data: file = semwise_nonbinary.dat; model: brand2 by y1@-0.5 y2@-0.5 y3@-0.5 y4@1 y5@1 y6@1 y7@0 y8@0 y9@0 ; brand3 by y1@-0.5 y2@-0.5 y3@-0.5 y4@0 y5@0 y6@0 y7@1 y8@1 y9@1 ; price by y1@-1 y2*0.2 y3@1 y4@-1 y5*0.2 y6@1 y7@-1 y8*0.2 y9@1 ; price by y2 y5 y8 (b); [y1-y9@0]; [brand2 brand3 price];</pre>	<pre>#Example 2 data analysis; #nonbinary SEMWISE analysis; semwise_nonbinary <- read.table("semwise_nonbinary.dat") names(semwise_nonbinary)<- c("y1","y2","y3","y4","y5","y6","y7","y8", "y9") model <- ' brand2 =~ -.5*y1 + -.5*y2 + -.5*y3 + 1*y4 + 1*y5 + 1*y6 + 0*y7 + 0*y8 + 0*y9 brand3 =~ -.5*y1 + -.5*y2 + -.5*y3 + 0*y4 + 0*y5 + 0*y6 + 1*y7 + 1*y8 + 1*y9 price =~ -1*y1 + b*y2 + 1*y3 + -1*y4 + b*y5 + 1*y6 + -1*y7 + b*y8 + 1*y9 y1 -0*1 y2 -0*1 y3 -0*1 y4 -0*1 y5 -0*1 y6 -0*1 y7 -0*1 y8 -0*1 y9 -0*1 brand2~1 brand3~1 price~1 '</pre> <pre>fit <- sem(model, data=semwise_nonbinary, meanstructure = TRUE) summary(fit)</pre>	<pre>!Example 2 data analysis; Nonbinary SEMWISE analysis DA NI=9 NO=0 LA y1 y2 y3 y4 y5 y6 y7 y8 y9 RA FI= semwise_nonbinary.dat MO NY=9 NE=3 LY=FR TE=DI,FR AL=FR PS=SY,FR BE=ZE TY=ZE PA LY 0 0 0 0 0 2 0 0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 2 0 0 0 MA LY -0.5 -0.5 -1.0 -0.5 -0.5 0.0 -0.5 -0.5 1.0 1.0 0.0 -1.0 1.0 0.0 0.0 1.0 0.0 1.0 0.0 1.0 -1.0 0.0 1.0 0.0 0.0 1.0 1.0 LE brand2 brand3 price OU MI SC</pre>

<pre>!Example 3 data generation; Title: Two methods SEMWISE data generation (Figure 3); montecarlo; names = y1-y8 z1-z8; nobs = 500; save = semwise2methods.dat; model population; My by y1-y8@1; Mz by z1-z8@1; eta1 by y1@1 z1@1.2; eta2 by y2@1 z2@1.2; eta3 by y3@1 z3@1.2; eta4 by y4@1 z4@1.2; eta5 by y5@1 z5@1.2; eta6 by y6@1 z6@1.2; eta7 by y7@1 z7@1.2; eta8 by y8@1 z8@1.2; ksi1 by eta1@-1 eta2@-1 eta3@-1 eta4@-1 eta5@1 eta6@1 eta7@1 eta8@1; ksi2 by eta1@-1 eta2@-1 eta3@1 eta4@1 eta5@-1 eta6@-1 eta7@1 eta8@1; ksi3 by eta1@-1 eta2@-1 eta3@1 eta4@1 eta5@1 eta6@1 eta7@-1 eta8@-1; ksi4 by eta1@-1 eta2@1 eta3@-1 eta4@1 eta5@-1 eta6@1 eta7@-1 eta8@1; ksi1-ksi4*.8; ksi1 with ksi2*.1 ksi3*.1 ksi4*.1; ksi2 with ksi3*.1 ksi4*.1; ksi3 with ksi4*.1; y1-y8*.2; z1-z8*.3; My*.2 Mz*.2; My with Mz*.1; My Mz with ksi1-ksi4@0; eta1-eta8*.2; [z1-z8@0]; [eta1-eta8@0]; [My*0 Mz*0];</pre>	<pre>!Example 3 data analysis; Title: Two methods SEMWISE data analysis (Figure 3); data: file = semwise2methods.dat; variable: names = y1-y8 z1-z8; model; My by y1-y8@1; Mz by z1-z8@1; eta1 by y1@1 z1(b); eta2 by y2@1 z2(b); eta3 by y3@1 z3(b); eta4 by y4@1 z4(b); eta5 by y5@1 z5(b); eta6 by y6@1 z6(b); eta7 by y7@1 z7(b); eta8 by y8@1 z8(b); KSI1 by eta1@-1 eta2@-1 eta3@-1 eta4@-1 eta5@1 eta6@1 eta7@1 eta8@1; KSI2 by eta1@-1 eta2@-1 eta3@1 eta4@1 eta5@-1 eta6@-1 eta7@1 eta8@1; KSI3 by eta1@-1 eta2@-1 eta3@1 eta4@1 eta5@1 eta6@1 eta7@-1 eta8@-1; KSI4 by eta1@-1 eta2@1 eta3@-1 eta4@1 eta5@-1 eta6@1 eta7@-1 eta8@1; My with ksi1-ksi4@0; Mz with ksi1-ksi4@0; [y1-y8@0]; [z1-z8@0]; [eta1-eta8@0]; [My*0 Mz*0]; [ksi1*.5 ksi2*.5 ksi3*-.25 ksi4*.25];</pre>	<pre>#Example 3 data analysis; #Two methods SEMWISE analysis; semwise2methods <- read.table("semwise2methods.dat") names(semwise2methods)<- c("y1","y2","y3","y4","y5","y6","y7","y8", "z1","z2","z3","z4","z5","z6","z7","z8") model <- 'My=-1*y1+1*y2+1*y3+1*y4+1*y5+1*y6+1*y7+ 1*y8 Mz=-1*z1+1*z2+1*z3+1*z4+1*z5+1*z6+1*z7+1 *z8 eta1 == 1*y1 + b*z1 eta2 == 1*y2 + b*z2 eta3 == 1*y3 + b*z3 eta4 == 1*y4 + b*z4 eta5 == 1*y5 + b*z5 eta6 == 1*y6 + b*z6 eta7 == 1*y7 + b*z7 eta8 == 1*y8 + b*z8 ksi1===-1*eta1+-1*eta2+-1*eta3+- 1*eta4+1*eta5+1*eta6+1*eta7+1*eta8 ksi2===-1*eta1+-1*eta2+1*eta3+1*eta4+- 1*eta5+-1*eta6+1*eta7+1*eta8 ksi3===-1*eta1+- 1*eta2+1*eta3+1*eta4+1*eta5+1*eta6+- 1*eta7+-1*eta8 ksi4===-1*eta1+1*eta2+-1*eta3+1*eta4+- 1*eta5+1*eta6+-1*eta7+1*eta8 My ~ 0*ksi1 My ~ 0*ksi2 My ~ 0*ksi3 My ~ 0*ksi4 Mz ~ 0*ksi1 Mz ~ 0*ksi2 Mz ~ 0*ksi3 Mz ~ 0*ksi4</pre>	<pre>!Example 3 data analysis; Two methods SEMWISE data analysis (Figure 3) DA NI=16 NO=0 LA y1 y2 y3 y4 y5 y6 y7 y8 z1 z2 z3 z4 z5 z6 z7 z8 RA FI = semwise2methods.dat MO NY=16 NE=10 NK=4 LY=FI TE=DI,FR AL=FI KA=FR PS=SY,FR GA=FI BE=ZE TY=ZE FR AL 9 AL 10 FR LY 9 1 LY 10 2 LY 11 3 LY 12 4 LY 13 5 LY 14 6 LY 15 7 LY 16 8 EQ LY 9 1 LY 10 2 LY 11 3 LY 12 4 LY 13 5 LY 14 6 LY 15 7 LY 16 8 MA LY 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 1 1 0 1 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 1 0 1 0 MA GA -1 -1 -1 -1 -1 -1 -1 1 -1 1 1 -1 -1 1 1 1 1 -1 1 -1 1 -1 1 1</pre>
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<pre>[ksi1*.5 ksi2*.5 ksi3*-.25 ksi4*.25];</pre>		<pre>y1 -0*1 y2 -0*1 y3 -0*1 y4 -0*1 y5 -0*1 y6 -0*1 y7 -0*1 y8 -0*1 z1 -0*1 z2 -0*1 z3 -0*1 z4 -0*1 z5 -0*1 z6 -0*1 z7 -0*1 z8 -0*1 eta1 -0*1 eta2 -0*1 eta3 -0*1 eta4 -0*1 eta5 -0*1 eta6 -0*1 eta7 -0*1 eta8 -0*1 My-1 Mz-1 ksi1~1 ksi2~1 ksi3~1 ksi4~1 '</pre> <pre>fit <- sem(model, data=semwise2methods, meanstructure = TRUE) summary(fit)</pre>	<pre>1 1 -1 -1 1 1 -1 1 0 0 0 0 0 0 0 0 PA PS 1 0 1 0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 1 LE eta1 eta2 eta3 eta4 eta5 eta6 eta7 eta8 My Mz LK ksi1 ksi2 ksi3 ksi4 OU MI SC</pre>
<pre>!Example 4 data generation; Title: Two-group SEMWISE mimic (see Figure 4); montecarlo: names = y1-y8;</pre>	<pre>!Example 4a data analysis; Title: SEMWISE analysis using binary covariate (Figure 4a); data: file = semwise2g.dat; variable:</pre>	<pre>#Example 4a data analysis; #SEMWISE analysis using binary covariate (Figure 4a) semwise2g <- read.table("semwise2g.dat") names(semwise2g)<-</pre>	<pre>!Example 4a data analysis; SEMWISE analysis using binary covariate (Figure 4a) DA NI=9 NO=0 LA</pre>

<pre> ngroups = 2; nobs = 250 250; save = semwise2g.dat; model population: eta0 by y1-y8@1; eta1 by y1@1 y2@1 y3@1 y4@1 y5@-1 y6@-1 y7@-1 y8@-1; eta2 by y1@-1 y2@-1 y3@1 y4@1 y5@-1 y6@-1 y7@1 y8@1; eta3 by y1@1 y2@-1 y3@1 y4@-1 y5@1 y6@-1 y7@1 y8@-1; eta0-eta3*.7; eta0 with eta1*.1; eta0 with eta2*.1; eta0 with eta3*.1; eta1 with eta2*.1; eta1 with eta3*.1; eta2 with eta3*.1; y1-y8*.2; model population-g2: eta0*1; [eta0*.5]; eta1-eta3*.25; [eta1*-.25 eta2*-.5]; y1-y8*.8; </pre>	<pre> names = y1-y8 g; define: g = g-1; model: eta0 by y1-y8@1; eta1 by y1@1 y2@1 y3@1 y4@1 y5@-1 y6@- 1 y7@-1 y8@-1; eta2 by y1@-1 y2@-1 y3@1 y4@1 y5@-1 y6@-1 y7@1 y8@1; eta3 by y1@1 y2@-1 y3@1 y4@-1 y5@1 y6@- 1 y7@1 y8@-1; eta0-eta3*.7; eta0 with eta1*.1; eta0 with eta2*.1; eta0 with eta3*.1; eta1 with eta2*.1; eta1 with eta3*.1; eta2 with eta3*.1; y1-y8*.5; eta0-eta3 on g; [y1-y8@0]; [eta0-eta3]; !Example 4b data analysis; Title: Two-group SEMWISE (Figure 4c); data: file = semwise2g.dat; variable: names = y1-y8 g; grouping = g (1 = male 2 = female); model: eta0 by y1-y8@1; eta1 by y1@1 y2@1 y3@1 y4@1 y5@-1 y6@- 1 y7@-1 y8@-1; eta2 by y1@-1 y2@-1 y3@1 y4@1 y5@-1 y6@-1 y7@1 y8@1; eta3 by y1@1 y2@-1 y3@1 y4@-1 y5@1 y6@- 1 y7@1 y8@-1; eta0-eta3*.7; eta0 with eta1*.1; eta0 with eta2*.1; </pre>	<pre> c("y1","y2","y3","y4","y5","y6","y7","y8", "g") semwise2g[,9] <- semwise2g[,9]-1 model <- ' eta0=-1*y1+1*y2+1*y3+1*y4+1*y5+1*y6+1*y7 +1*y8 eta1=-1*y1+1*y2+1*y3+1*y4+-1*y5+-1*y6+- 1*y7+-1*y8 eta2=-1*y1+-1*y2+1*y3+1*y4+-1*y5+- 1*y6+1*y7+1*y8 eta3=-1*y1+-1*y2+1*y3+-1*y4+1*y5+- 1*y6+1*y7+-1*y8 eta0 ~ g eta1 ~ g eta2 ~ g eta3 ~ g y1 -0*1 y2 -0*1 y3 -0*1 y4 -0*1 y5 -0*1 y6 -0*1 y7 -0*1 y8 -0*1 eta0~1 eta1~1 eta2~1 eta3~1 ' fit <- sem(model, data=semwise2g, meanstructure = TRUE) summary(fit) #Example 4b data analysis; #SEMWISE analysis using binary covariate (Figure 4c) semwise2g <- read.table("semwise2g.dat") names(semwise2g)<- c("y1","y2","y3","y4","y5","y6","y7","y8", "g") model <- ' </pre>	<pre> y1 y2 y3 y4 y5 y6 y7 y8 g RA FI= semwise2g.dat MO NY=8 NX=1 NE=4 LY=FI TE=DI,FR KA=FR AL=FR PS=SY,FR BE=ZE TY=ZE FI MA LY 1 1 -1 1 1 1 -1 -1 1 1 1 1 1 1 1 -1 1 -1 -1 1 1 -1 -1 -1 1 -1 1 1 1 -1 1 -1 FR GA 1 1 GA 2 1 GA 3 1 GA 4 1 LE eta0 eta1 eta2 eta3 OU MI SC !Example 4b data analysis; Two-group SEMWISE (Figure 4c) - Males DA NI=9 NO=250 NG=2 LA y1 y2 y3 y4 y5 y6 y7 y8 g RA FI=semwise2g-m.dat SE 1 2 3 4 5 6 7 8/ MO NY=8 NE=4 LY=FI TE=DI,FR AL=FR PS=SY,FR BE=ZE TY=ZE MA LY 1 1 -1 1 1 1 -1 -1 1 1 1 1 1 1 1 -1 1 -1 -1 1 1 -1 -1 -1 1 -1 1 1 1 -1 1 -1 LE eta0 eta1 eta2 eta3 </pre>
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	<pre>eta0 with eta3*.1; eta1 with eta2*.1; eta1 with eta3*.1; eta2 with eta3*.1; y1-y8*.5; [y1-y8@0]; model male:[eta0-eta3]; model female:[eta0-eta3];</pre>	<pre>eta0=-1*y1+1*y2+1*y3+1*y4+1*y5+1*y6+1*y7 +1*y8 eta1=-1*y1+1*y2+1*y3+1*y4+-1*y5+-1*y6+- 1*y7+-1*y8 eta2=-1*y1+-1*y2+1*y3+1*y4+-1*y5+- 1*y6+1*y7+1*y8 eta3=-1*y1+-1*y2+1*y3+-1*y4+1*y5+- 1*y6+1*y7+-1*y8 y1 -0*1 y2 -0*1 y3 -0*1 y4 -0*1 y5 -0*1 y6 -0*1 y7 -0*1 y8 -0*1 eta0-1 eta1-1 eta2-1 eta3-1 ' fit <- sem(model, data=semwise2g, meanstructure = TRUE, group = "g") summary(fit)</pre>	<pre>OU MI SC Two-group SEMWISE (Figure 4c) - Females DA NI=9 NO=250 LA y1 y2 y3 y4 y5 y6 y7 y8 g RA FI=semwise2g-f.dat SE 1 2 3 4 5 6 7 8/ MO NY=8 NE=4 LY=FI TE=DI,FR AL=FR PS=SY,FR BE=ZE TY=ZE MA LY 1 1 -1 1 1 1 -1 -1 1 1 1 1 1 1 1 -1 1 -1 -1 1 1 -1 -1 -1 1 -1 1 1 1 -1 1 -1 LE eta0 eta1 eta2 eta3 OU MI SC</pre>
<pre>!Example 5 data generation; Title: SEMWISE with outcome data generation (Figure 4a and 4b); montecarlo: names = outcome y1-y4 x; nobs = 500; nreps = 1; save = semwise_mediation.dat; model population: model population: eta0 by y1-y4@1; eta1 by y1@1 y2@-1 y3@1 y4@-1; eta2 by y1@1 y2@1 y3@-1 y4@-1; y1-y4*.2; eta0*1 eta1*.96 eta2*.84;</pre>	<pre>!Example 5 data analysis; Title: SEMWISE with outcome data analysis (Figure 4a and 4b); data: file = semwise_mediation.dat; variable: names = outcome y1-y4 x; model: eta0 by y1-y4@1; eta1 by y1@1 y2@-1 y3@1 y4@-1; eta2 by y1@1 y2@1 y3@-1 y4@-1; outcome on eta0-eta2; [y1-y4@0]; [eta0-eta2]; [x]; eta0-eta2 with eta0-eta2*0; eta0-eta2 on x;</pre>	<pre>#Example 5 data analysis; #SEMWISE with outcome data analysis (Figure 4a and 4b) semwise_mediation <- read.table("semwise_mediation.dat") names(semwise_mediation)<- c("outcome", "y1", "y2", "y3", "y4", "x") model <- ' eta1=-1*y1+1*y2+1*y3+1*y4 eta2=-1*y1+-1*y2+1*y3+-1*y4 eta3=-1*y1+1*y2+-1*y3+-1*y4 outcome ~ eta1 + eta2 + eta3 eta1 ~ x eta2 ~ x eta3 ~ x</pre>	<pre>!Example 5 data analysis; SEMWISE with outcome data analysis (Figure 4a and 4b) DA NI=6 NO=0 LA outcome y1 y2 y3 y4 x RA FI= semwise_mediation.dat SE 2 3 4 5 1 6/ MO NY=5 NX=1 NE=4 LY=FI TE=DI,FR KA=FR AL=FR GA=FR TY=ZE PS=SY BE=FI FI MA LY 1 1 1 0 1 -1 1 0</pre>

<pre>eta0-eta2 with eta0-eta2*0; outcome on eta0*0 eta1*.6 eta2*-.4; outcome*.5; eta0 on x*0; eta1 on x*.2; eta2 on x*.4; [x*0]; x*1;</pre>		<pre>y1~0*1 y2~0*1 y3~0*1 y4~0*1 eta1~1 eta2~1 eta3~1 eta2 ~~ eta1 eta3 ~~ eta1 eta3 ~~ eta2 ' fit <- sem(model, data=semwise_mediation, meanstructure = TRUE) summary(fit)</pre>	<pre>1 1 -1 0 1 -1 -1 0 0 0 0 1 FI GA 4 1 FR BE 4 1 BE 4 2 BE 4 3 PA PS 1 1 1 1 1 1 0 0 0 1 FI TE 5 5 LE eta0 eta1 eta2 outcome OU MI SC</pre>
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